Teaching Humanoids to Imitate 'Shapes' of Movements

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Abstract. Trajectory formation is one of the basic functions of the neuromotor controller. In particular, reaching, avoiding, controlling impacts (hitting), drawing, dancing and imitating are motion paradigms that result in formation of spatiotemporal trajectories of different degrees of complexity. Transferring some of these skills to humanoids allows us to understand how we ourselves learn, store and importantly, generalize motor behavior (to new contexts). Using the playful scenario of teaching baby humanoid iCub to 'draw', the essential set of transformations necessary to enable the student to 'swiftly' enact a teachers demonstration are investigated in this paper. A crucial feature in the proposed architecture is that, what iCub learns to imitate is not the teachers 'end effector trajectories' but rather their 'shapes'. The resulting advantages are numerous. The extracted 'Shape' being a high level representation of the teachers movement, endows the learnt action natural invariance wrt scale, location, orientation and the end effector used in its creation (ex. it becomes possible to draw a circle on a piece of paper or run a circle in a football field based on the internal body model to which the learnt attractor is coupled). The first few scribbles generated by iCub while learning to draw primitive shapes being taught to it are presented. Finally, teaching iCub to draw opens new avenues for iCub to both gradually build its mental concepts of things (a star, house, moon, face etc) and begin to communicate with the human partner in one of the most predominant ways humans communicate i.e. by writing.

Keywords: Shape, Imitation, iCub, Passive Motion Paradigm, Catastrophe theory

1 Introduction

Behind all our incessant perception-actions underlies the core cognitive faculty of 'perceiving and synthesizing' shape. Perceiving affordances of objects in the environment for example a cylinder, a ball, etc, or performing movements ourselves, shaping ones fingers while manipulating objects, reading, drawing or imitating are some examples. Surprisingly, it is not easy to define 'shape' quantitatively or even express it in mensurational quantities. Vaguely, shape is the core information in any object/action that survives the effects of changes in location, scale, orientation, end effectors/bodies used in its creation, and even minor structural injury. It is infact this invariance that makes the abstract notion of 'shape' a crucial information in all our

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sensorimotor interactions. How do humans effortlessly perceive and synthesize 'shape' during their daily activities and what are the essential set of computational transformations that would enable humanoids to do the same? In this paper, we describe our attempts to understand this multidimensional problem using the scenario of teaching baby humanoid iCub to draw shapes on a drawing board after observing a demonstration and aided by a series of self evaluations of its performance.

It is quite evident that scenario of iCub learning to draw a trajectory after observing a teachers demonstration embeds the central loop of imitation i.e transformation from the visual perception of a teacher to motor commands of a student. The social, cultural and cognitive implications of imitation are well documented in literature today [9, 11-12]. In the recent years, a number of interesting computational approaches like direct policy learning, model based learning, learning attractor landscapes using dynamical systems [4] have been proposed to tackle parts of the imitation learning problem [12]. Based on the fact that usually a teacher's demonstration provides a rather limited amount of data, best described as "sample trajectories", various projects investigated how a stable policy can be instantiated from such small amount of information. The major advancement in these schemes was that the demonstration is used just as a starting point to further learn the task by self improvement. In most cases, demonstrations were usually recorded using marker based optical recording and then either spline based techniques or dynamical systems were used to approximate the trajectories. Compared to spline based techniques, the dynamical systems based approach have the advantage of being temporally invariant (because splines are explicitly parameterized in time) and naturally resistant to perturbations. The approach has been has been successfully applied in different imitation scenarios like learning the kendama game, tennis stokes, drumming, generating movement sequences with an anthropomorphic robot [2].

The approach proposed in this paper is also based on nonlinear attractor dynamics and has the flavour of self improvement, temporal invariance (through terminal attractor dynamics [15]) and generalization to novel task specific constraints. However, we also go beyond this in the sense that what iCub learns to imitate is the 'Shape' a rather high level invariant representation extracted from the demonstration. It is independent of scale, location, orientation, time and also the end effector/body chain that creates it (for example, we may draw a circle on a piece of paper or run a circle in a football field). The eyes of iCub are the only source of gathering information about the demonstration. No additional optical marker equipments recording all joint angles of the teacher are employed. In any case, very use of joint information for motion approximation/generation makes it difficult to generalize the learnt action to a different body chain, which is possible from the high level action representations acquired using our approach. Figure 1 shows the high level information flows between different sub modules in the loop starting from the teachers demonstration and culminating in iCub learning to perform the same. The perceptual subsystems are shown in pink background, the motor subsystems in blue and learning modules in green. Section 2 briefly summarizes the perceptual modules that ultimately lead to the creation of a motor goal in iCub's brain. Section 3 and 4 focus on the central issue of this paper about how iCub learns to realize this motor goal (i.e. imitate the teachers' performance), along with experimental results. A brief discussion concludes.

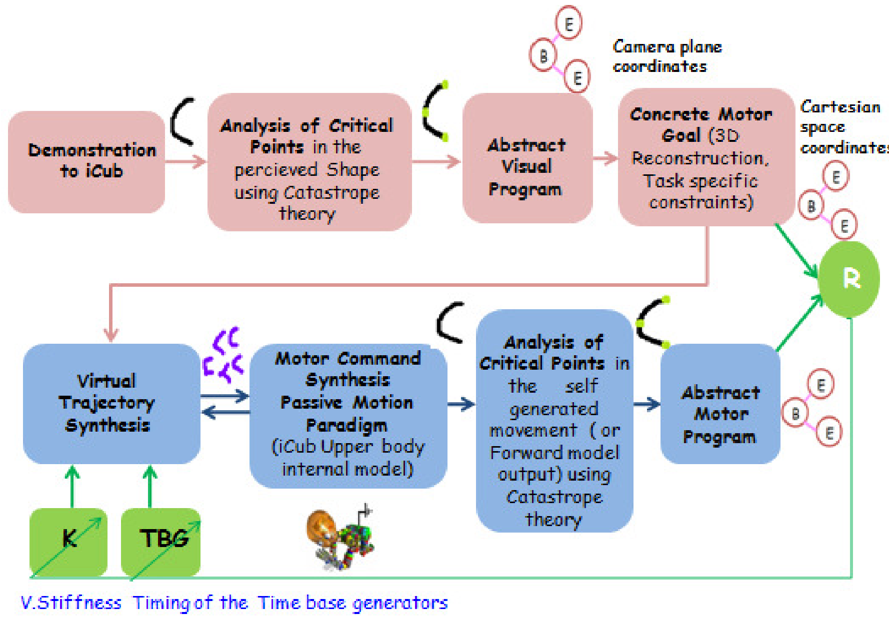

Figure1 shows the overall high level information flows in the proposed architecture, beginning with the demonstration to iCub (for example a 'C'). A preprocessing phase extracts the teachers end effector trajectory from the demonstration. This is followed by characterization of the 'shape' of the extracted trajectory using Catastrophe theory [13-14], that leads to the creation of an abstract visual program (AVP). Since the AVP is created out of visual information coming from the two cameras, it is represented in camera plane coordinates. Firstly we need to reconstruct this information to iCub's ego centric frame of reference. Other necessary task specific constraints (like, prescription of scale, end effector/body chain involved in the motor action etc) are also applied at this phase. In this way, the context independent AVP is transformed into a concrete motor goal for iCub to realize. CMG forms the input of the virtual trajectory generation system (VTGS) that synthesizes different virtual trajectories by pseudo randomly exploring the space of virtual stiffness (K) and timing (TBG). These virtual trajectories act as attractors and can be coupled to the relevant internal body model of iCub to synthesize the motor commands for action generation (using Passive Motion Paradigm [5]). In the experiments presented in this paper, the torso-left arm-paint brush chain of iCub is employed. Analysis of the forward model output once again using catastrophe theory extracts the 'shape' of the self generated movement. This is called as the Abstract motor program. Abstract visual and motor information can now be directly compared to self evaluate a score of performance. A learning loop follows.

2 Extracting the 'Shape' of a visually observed end effector movements (of self and others)

As seen in figure 1, the stimulus to begin with is the teacher's demonstration. This demonstration is usually composed of a sequence of strokes, each stroke tracing a finite, continuous line segment inside the visual workspace of both cameras. These strokes are created using a green pen i.e. the optical marker iCub track. The captured video of the demonstration undergoes a preprocessing stage, where the location of the marker in each frame (for both camera outputs) is detected using a simple colour segmentation module. If there are N frames in the captured demonstration, the information at the end of the pre-processing phase is organized in the form of a Nx4 matrix, N^{th} row containing the detected location of the marker (U_{left},V_{left} ,U_{right},V_{right}) in the left and right cameras during the N^{th} frame. In this way the complete trajectory traced by the teacher (as observed in the camera plane coordinates) is extracted. The next stage is to create a abstract high level representation of this trajectory, by extracting its shape. A systematic treatment of the problem of shape can be found in a branch of mathematics known as Catastrophe theory (CT) originally proposed in late 1960's by French mathematician Rene Thom, further developed by Zeeman[14], Gilmore[3] among others and applied to a range of problems in engineering and physics. According to CT the overall shape of a smooth function, f(x), is determined by special local features like ''peaks'', ''valleys'' etc called as critical points (CP). When all the CP of a function is known, we know its global shape. Further developing CT, [1] have shown that following 12 CP's (pictorially shown in figure 2a) are sufficient to characterize the shape of any line diagram: Interior Point, End Point, Bump (i.e maxima or minima), Cusp, Dot, Cross, Contact, Star, Angle, Wiggle, T and Peck. These 12 critical points, found in many of the worlds scripts, can be computed very easily using simple mathematical operations [1]. In this way the shape of the trajectory demonstrated by the teacher can be described using a set of critical points that describe its 'essence'. For example, the essence of the shape 'C' of figure 1, is the presence of a bump (maxima) in between the start and end points. As shown in figure 2b, for any complex trajectory, the shape description takes the form of a graph with different CP at the graph nodes.

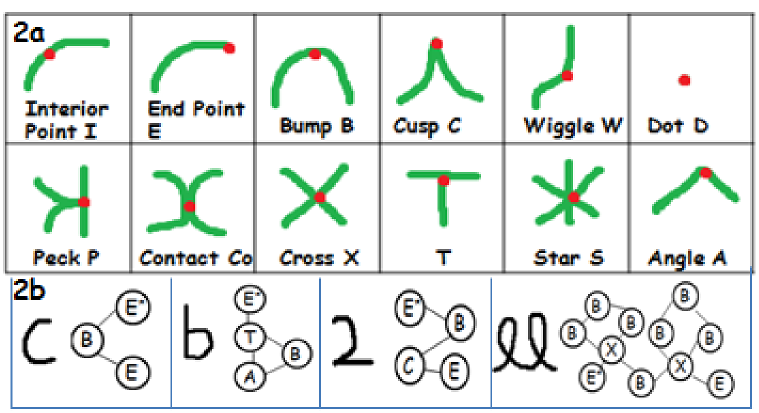

Figure 2a. Pictorially illustrates the 12 primitive shape critical points derived in [1] using catastrophe theory. Figure 2b. Shows the extracted shape descriptors for four demonstrated trajectories.

By extracting the shape descriptors, we have effectively reduced the complete demonstrated trajectory to a small set of critical points (their type and location in camera plane coordinates). We call this compact representation as the abstract visual program (AVP). AVP may be thought as a high level visual goal created in iCub's brain after perceiving the teachers demonstration. To facilitate any action generation to take place, this visual goal must be transformed into an appropriate motor goal in iCub's egocentric space. To achieve this, we have to transform location of the shape critical points computed in the image planes of the two cameras (U_{left}, V_{left} , U_{right}, V_{right}) into corresponding points in the iCub's egocentric space (x,y,z) by a process of 3D reconstruction. Of course the 'type' of the CP is conserved i.e a bump/maxima still remains a bump, a cross is still a cross in any coordinate frame. Reconstruction is achieved using Direct Linear Transform (Shapiro, 1978) based stereo camera calibration and 3D reconstruction system [8] already functional in iCub [5-6]. The set of transformations leading to the formation of the Concrete motor goal is pictorially shown in figure 3. Also note that since critical points analysis using CT can be used to extract shapes of trajectories in general, the same module is reused to extract the shape of iCub's end effector trajectory (as predicted by the forward model) during action generation process. This is called as the abstract motor program (AMP). Since AMP and CMG contain shape description (and also in the same frame of reference), they can directly be compared to evaluate performance and trigger learning in the right direction.

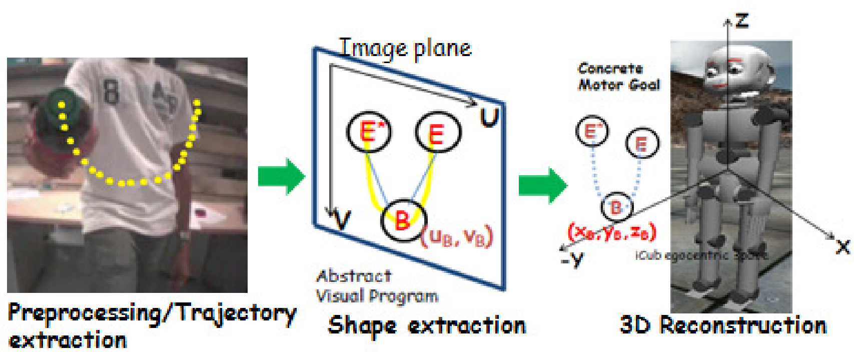

Figure 3. Pictorially shows the set of transformations leading to the formation of concrete motor goal.

3 Virtual Trajectory Synthesis and Learning to Shape

The CMG basically consists of a discrete set of critical points (their location in iCub's ego centric space and type), that describe in abstract terms the 'shape' iCub must now create itself. For example, the CMG of the shape 'U' (figure 3) has three CP's (2 end points 'E', and one bump 'B' in between them). Given any two points in space, an infinite number of trajectories can be shaped passing through them. How can iCub learn to synthesize a continuous trajectory similar to the demonstrated shape using a discrete set of critical points in the CMG? In this section we seek to answer this question.

The first step in this direction is the synthesis of virtual trajectory between the shape critical points in the CMG. Synthesized virtual trajectories do not really exist in space and must not be confused with the actual shapes drawn by iCub. Instead, they act as attractors and play a significant role in the generation of the motor action that creates the shape. Let $X_{ini} \epsilon (x,y,z)$ be the initial condition i.e. the point in space from where the creation of shape is expected to commence (usually initial condition will be one of the end points in CMG). If there are N CP's in the CMG, the spatiotemporal evolution of virtual trajectory (x,y,z,t) is equivalent to integrating a non-linear differential equation that takes the following form:

$$\begin{cases} \dot{\boldsymbol{x}}_{ini} = \sum_{i=1}^{N} K_i \gamma_i(t) \cdot \left(\boldsymbol{x}_{CP_i} - \boldsymbol{x}_{ini}\right) \\ \gamma(t) = \dfrac{\dot{\xi}}{1-\xi} \\ \xi(t) = 6\left(\dfrac{t}{\tau}\right)^5 - 15\left(\dfrac{t}{\tau}\right)^4 + 10\left(\dfrac{t}{\tau}\right)^3 \end{cases} \tag{1}$$

Intuitively, as seen in figure 4, we may visualize X_{ini} as connected to all the shape CP's in the CMG by means of virtual springs and hence being attracted by the force fields generated by them $F_{CP}=K_{CP}(x_{CP}-x_{ini})$. The strength of these attractive force fields depends on: 1) the virtual stiffness 'K_i' of the spring and 2) time varying modulatory signals $\gamma_i(t)$ generated by their respective time base generators (TBG), that basically weigh the influence of different CP's through time. Note that he function $\gamma(t)$ implements the terminal attractor dynamics [15], a mechanism to control the timing of the relaxation of a dynamical system to equilibrium. The function $\xi(t)$ is a minimum jerk time base generator . The virtual trajectory is the set of equilibrium points created during the evolution X_{ini} through time, under the influence of the net attractive field generated by different CP's. Further, by simulating the dynamics of equation 1, with different values of K and γ, a wide range of virtual trajectories can be obtained passing through the CP's. Inversely, learning to 'shape' translates into the problem of learning the right set of virtual stiffness and timing such that the 'Shape' of the trajectory created by iCub correlates with the shape description in CMG.

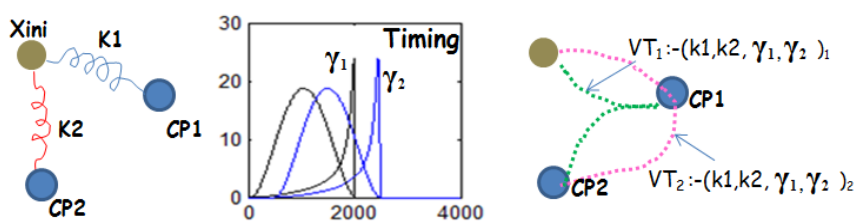

Figure 4. Intuitively, we may visualize X_{ini} as connected to all the shape CP's in the CMG by means of virtual springs. The attractive fields exerted by different CP's at different instances of time is a function of the virtual stiffness (k) and the timing signal γ of the time base generator. The virtual trajectory is the set of equilibrium points created during the evolution X_{ini} through time, under the influence of the net attractive field generated by different CP's. For different sets of K and γ we get different virtual trajectories.

The site of learning i.e virtual stiffness matrix 'K' of equation 1 are basically open parameters (positive definite). One may intuitively imagine the procedure of estimating the correct values of 'K' analogous to a manual eye testing scenario, where the optician is faced with the problem of estimating the right optical power of the eye glasses necessary for a patient. Just by exploring a fixed range of test lenses, and aided by the feedback of the patient, the optician is able to quickly estimate the dioptric value of the lens required for the patient. Since this procedure is mainly pseudorandom exploration, questions regarding convergence and fast learning are critical. The answer lies in inherent modularity in our architecture. Once iCub learns to draw the 12 shape primitives of figure 2a, it can exploit this motor knowledge to compose more complex shapes (that can be described as combinations of these primitive shape features as in figure 2b). Moreover, using a bump, cusp and straight line all other primitives of 2a can be created (example, peck is a composition of straight line and cusp and so on). Hence once iCub learns to draw a straight line, bump and cusp it can exploit this motor knowledge to draw the other shape primitives, and this can be further exploited during the creation of more complex line diagrams.

Considering that the behaviour of neuromuscular system is predominantly spring like, we consider only symmetric stiffness matrix K, with all non diagonal elements zero (In other words, the resulting vector fields have zero curl). Regarding straight lines, it is well known that human reaching movements follow straight line trajectories with a bell shaped velocity profile. This can be achieved in the VTGS by keeping components of matrix K equal in equation 1 ($K_{xx}=K_{yy}=K_{zz}$). More curved trajectories can be obtained otherwise. Figure 5 shows some of the virtual trajectories generated by titillating the components of the K matrix numerically from 1-9 and simulating the dynamics of equation 1. As seen, a gamut of shapes, most importantly cusps and bumps can be synthesized by exploring this small range itself. Essentially what matters is not the individual values of the components, but the balance between them which goes on to shape the net attractive force field to the CP. Once iCub learns to draw straight lines, bumps and cusps, it can exploit this motor knowledge to learn the other primitives, and through 'composition' any complex shape.

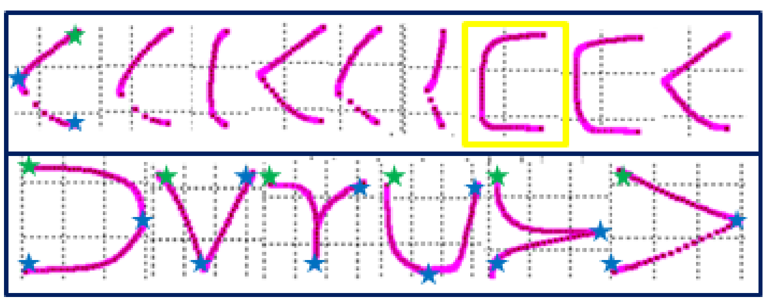

Figure 5. Top Panel shows the range of virtual trajectories synthesized while learning do draw a 'C', with the best solution highlighted. Bottom panel shows other goal shapes learnt. All these shapes can be created by pseudo randomly titillating the components of the matrix K in the fixed range of 1-9.

4 Motor Command Synthesis: Coupled Interactions between the Virtual Trajectory and Internal body model

In this section, we deal with the final problem of motor command synthesis, that will ultimately transform the learnt virtual trajectory into a real trajectory created by iCub. We use the passive motion paradigm (PMP) based forward/inverse model for upper body coordination of iCub (figure 6) in the action generation phase [5-6]. This interface between the virtual trajectory and the PMP based iCub internal body model is similar to the coordination of the movements of a puppet, virtual trajectory playing the role of the puppeteer. As the strings pull the finger tip of the puppet to the target, the rest of the body elastically reconfigures to achieve a posture that is necessary to position the end effector to the target. If motor commands (trajectory of joint angles) derived by this process of relaxation is actively fed to the actuators, iCub will physically create the shape (hence transforming the virtual trajectory into a real trajectory). This is the central hypothesis behind the VTGS-PMP coupling. The evolving virtual trajectory generates an attractive force field $F=K(x_{VT}-x)$ applied at the end effector, hence leading the end effector to track it (figure 7, top left panel). This field is mapped from the extrinsic to the intrinsic space by means of the mapping $T=J^{T}F$ that yields an attractive torque field in the intrinsic space (J is the Jacobian matrix of the kinematic transformation). The total torque field induces a coordinated motion of all the joints in the intrinsic space according to an admittance matrix A. The motion of the joints now, determines the motion of the end-effector according to the following relationship: $\dot{x} = J\,\dot{q}$. Ultimately, the motion of the kinematic chain evoked by the evolving VT is equivalent to integrating non-linear differential equations that, in the simplest case in which there are no additional constraints, takes the following form:

$$\dot{x} = \Gamma(t)\, J\, A\, J^{T}\, K\left(x_{VT} - x\right) \qquad (2)$$

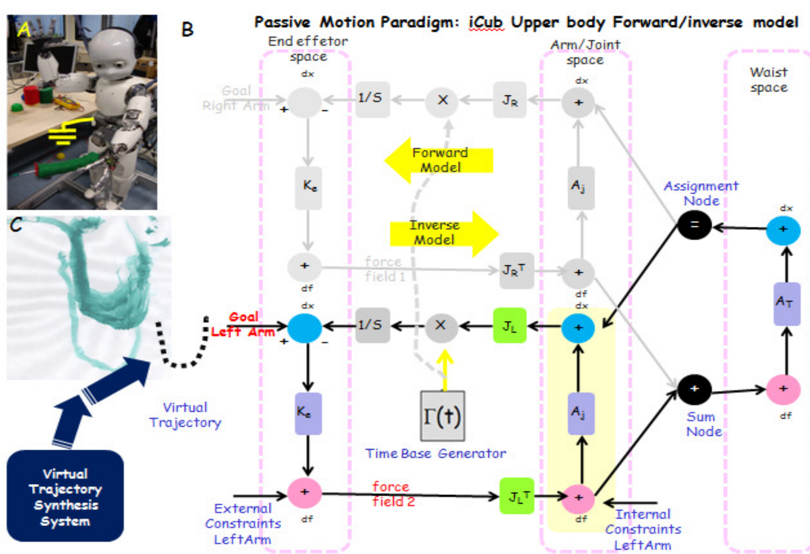

Figure 6. The PMP Forward/Inverse model for iCub upper body coordination. The torso/left arm chain is used in the iCub drawing experiments (Panel A), hence the right arm chain is deactivated. The evolving virtual trajectory acts as an attractor to the PMP system and triggers the synthesis of motor commands (This process is analogous to the coordinating a puppet, the VT serving the role of the puppeteer). Panel C shows the scanned image of drawings of iCub while learning to draw a ‘U’.

At the end of the PMP relaxation, we get two trajectories, a trajectory of joint angles (10 DoF (3 torso and 7 left arm) X 3000 iterations in time) and the end effector trajectory (predicted forward model output as a consequence of the motor commands, which is used for monitoring and performance evaluation). As seen in the results of figure 7, when the motor commands are buffered to the actuators, iCub creates the shape, hence transforming the virtual trajectory into a real trajectory (drawn by it).

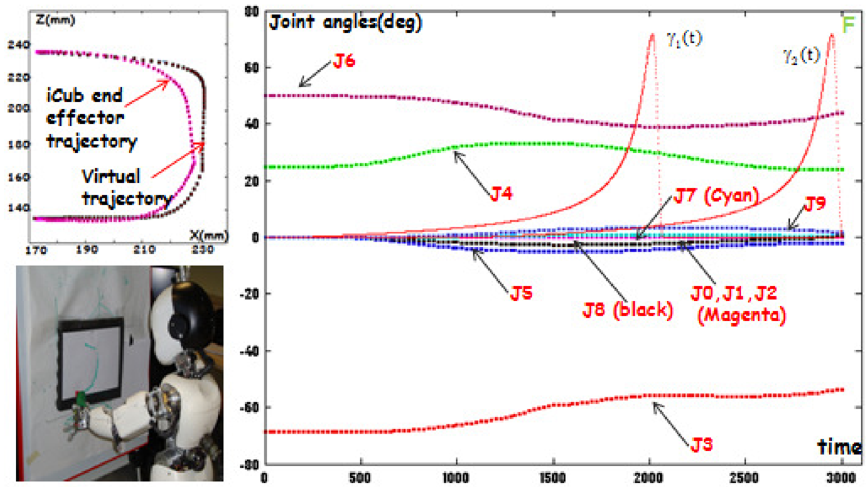

Figure 7a. Top left panel shows both the learnt virtual trajectory (attractor) and iCub's end effector trajectory (predicted forward model output) as a result of the motor commands derived using PMP (10 DoF torso/left arm chain X 3000 iterations in time). Bottom left panel shows iCub drawing the shape. The drawing were created on a drawing board, with paper attached to a layer of soft foam. The foam and the bristles of the paint brush provide natural compliance and allow safe interaction.

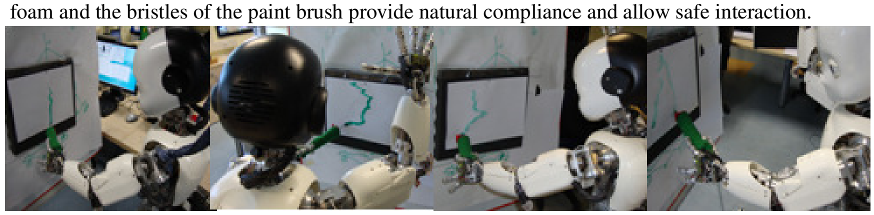

Figure 7b. The first 'scribbles'

5 Discussion

Using the scenario of gradually teaching iCub to draw, a minimal architecture that intricately couples the complementary operations of shape perception/synthesis in the framework of a 'teacher-learner' environment was presented in this article. The proposed action-perception loop also encompasses the central loop of imitation (specifically, end effector trajectories), with the difference that what iCub learns is not to reproduce a mere trajectory in 3D space by means of a specific end-effector but, more generally, to produce an infinite family of 'shapes' in any scale, in any position, using any possible end-effector/body part. We showed that by simulating the dynamics of VTGS using a fixed range of virtual stiffness' a diversity of shapes, mainly the primitives (derived using CT) can be synthesized. Since complex shapes can be efficiently ‘decomposed’ into combinations of primitive shapes (using CT), inversely the actions needed to synthesize them can ‘composed’ using combinations of the corresponding ‘learnt’ primitive actions. Ongoing experiments clearly show that motor knowledge gained while learning a ‘C’ and ‘U’ can be systematically exploited while learning to draw a ‘S’ and so on. Thus, there is a delicate balance between exploration and compositionality, the former dominating during the initial phases to learn the basics, the later dominating during the synthesis of more complex shapes. Finally, teaching iCub to draw opens new avenues for iCub to both gradually build its mental concepts of things (a star, house, moon, face etc) and begin to communicate with the human partner in one of the most predominant ways humans communicate i.e. by writing.

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